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The Impact and Mechanism of Digital Economy on Carbon Emission Efficiency: A Perspective Based on Provincial Panel Data in China

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Abstract: Using the Super-SBM method, this study calculates the carbon emission efficiency (CEE) of 30 provinces in mainland China from 2011 to 2019. Then, using the systematic GMM model, spatial Durbin model, and mediating effect model, it examines the direct effect, spatial effect, and influence mechanism of the digital economy (DE) on CEE. It was found that (1) the DE significantly promoted regional CEE, but had a negative effect on CEE in provinces with high economic correlation; (2) mechanism studies showed that the DE improved CEE by reducing energy intensity, promoting industrial upgrading and green technology innovation; (3) regional heterogeneity analysis found that the DE significantly improved CEE in eastern provinces, but not in central and western provinces. DE improves CEE in provinces with high level of economic development, but decreases CEE in provinces with low level of economic development.This paper provides some empirical and theoretical references for the development of DE to improve CEE.

Keywords: digital economy; CE efficiency; systematic GMM model; spatial Durbin model

1. Introduction

As industrialization and urbanization continue to advance, human activities and rising energy demand have led to increasing carbon dioxide emissions, exacerbating a series of climate chain reactions characterized by climate warming (Ge et al., 2022). China has promised to vigorously battle climate change, commit to energy saving and emission reduction, and honor the Paris Agreement by reaching its carbon peak by roughly 2030 and becoming carbon neutral by 2060. This goal indicates that as China's ability to sustain its environment is dwindling, the traditional development model of not taking into account the environmental costs is now unsustainable, and full attention needs to be paid to total factor carbon productivity, which considers CE as non-desired outputs (Meng et al., 2016). By analyzing the reasons for efficient or inefficient regional CEE, CEE can indeed be enhanced through the rational use of facilitating factors and the rational elimination of inhibiting factors. To decrease CO2 and increase energy efficiency, so as to achieve the healthy and green development of economy and ecology. Therefore, each region can start from improving CEE to meet emission reduction targets by reducing CE.

The Internet, big data, and cloud computing are examples of A new breed of informatics involves things that has developed quickly in recent years, ushering in the digital era and giving rise to the DE, which has turn become one of the key development poles in the whole of the country's economy, and is manifesting its power and momentum at an unprecedented scale and speed (Zhang et al., 2022). The DE, also known as the information economy, is essentially a type of economy characterized by big data, cloud computing, the Internet of Things, and the three components of productivity (means of production, objects, and workers), which are the keys to digital empowerment, increased productivity, and smart manufacturing. Future investment will be focused

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on building and upgrading new generation information infrastructure as 2G falls behind, 3G imitates to catch up, 4G synchronizes, and 5G surpasses (Li et al., 2021), which calls for an increase in production efficiency and total factor allocation efficiency in order to further unleash social output while raising societal investment in the development of DE. A large number of reports have existed at home and abroad to conduct pertinent research and analysis on the status of construction of the DE, and these research are crucial for achieving the DE's high-quality and rapid development as well as for boosting the nation's overall economic power. However, there is a dearth of research on how the DE affects China's CE performance and its mode of action. In summary, under the aim of successfully achieving the double carbon target, studying the effect and mechanism of the DE on CEE is of major practical importance, in order to lead our country to alter the style of development, improve the industrial structure, and alter the growth momentum and thus build the DE to accomplish the sustainable development of energy efficiency, a low-carbon economy and emission reduction.

The following factors primarily highlight the essay's possible dedications. First, the literature on the impact of DE on CEE is expanded by using the systematic GMM model and the SDM to investigate the effects of DE on CEE. Secondly, this research examined the varied effects of the DE on CEE in various geographic regions and economic development level, which provides empirical references for the future DE to support the growth of a low-carbon economy in accordance with regional and economic development level needs. Finally, the mediating effect model is also employed to study the DE's mechanism of influence on CEE from the perspectives of energy intensity, industrial structure upgrading, and technological innovation.This model serves as a point of reference for future research on the manner in which the DE affects CEE.

2. Literature review and research hypothesis

To reach China's objective of becoming carbon neutral by 2060, CEE must be improved, which has received more and more attention from scholars domestically and abroad. In the previous related studies, the research direction and perspective emphasis primarily on three aspects, the definition of CEE, the measurement of CEE and the influencing factors. Generally, CEE is divided into single-factor CEE and full-factor CEE. The three basic categories used to classify Single-factor CEE. One is carbon productivity, which Kaya and Yokobori initially planned to express carbon productivity Considering the GDP to CE ratio (Kaya & Yokobori, 1997), i.e., the value of GDP generated per unit of CE. Second is the carbon index, which was put up by Mielnik and Goldemberg (1999) to evaluate CEE in terms of the proportion of overall energy use to overall CE, i.e., the CE for each unit of energy consumed. The third component is carbon intensity, or CE per unit of GDP growth (Ang, 1999). Because single-factor efficiency can only represent how energy and economics efficiency are related, ignoring the consideration of the effect of other factors like as capital, labor, and technology on the significance of economic growth (Lv et al., 2021), total factor productivity takes into account the situation of multiple inputs, and the calculation results are more scientific and reasonable than single-factor efficiency, scholars began to use the stochastic frontier analysis (SFA model) of parametric method and the non-parametric method of data envelopment analysis (DEA model) to mainly measure the total factor carbon efficiency to conduct research. In previous studies, it is generally agreed that openness to the outside world, government intervention, enterprise ownership structure, technological progress, and enterprise size has favorable effects on CEE, and economic size, energy consumption structure and industrial structure, urbanization rate, and endowment structure have greater negative effects on CEE (Sun & Huang, 2020; Yu & Zhang, 2021).

In the course of history, the DE has been successively presented as information economy, Internet economy and other forms, so it is difficult to give a simple definition from a certain aspect or aspects, and domestic and foreign studies still have not formed a unified concept definition of DE (Bukh & Heeks, 2017). With the growth of DE, international interest in the field of DE research has increased. The existing research mostly focuses on how the DE affects the economy and the environment. First, the economic effects of the DE are discussed and analyzed from various perspectives, including macro, micro, and scale measurement, with respect to their impact

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mechanisms. From a macro perspective, new input factors such as digital information generated by the construction of the DE will impact how well regional resources are distributed, and therefore, the development of the DE has an impact on the economic development, innovation efficiency, total factor productivity have a positive impact and are the core drivers for the region to attain high-quality economic growth (Ma et al., 2022; Goldfarb & Tucker,2019; Niyazbekova et al., 2021). Barata.(2019) argued that higher income and job growth brought on by the construction of the DE would be able to lower poverty and inequality in the long run as these benefits will further strengthen long-term sustainable national economic growth. Chakpitak et al.(2022) thought that Thailand has world and new in both the social and economic spheres due to the DE, and the anticipated results demonstrate that technology can have a positive impact on the Thai economy. Using panel data collected nationally from 2008 to 2018, Dong et al. (2022) found that the growth of the DE greatly decreased the intensity of the nation's CE, and that economic expansion, financial deepening, and modernization of the industrial structure acted as a mediating factor between the two. Studies conducted from a micro perspective are more detailed and have clearer impact mechanisms. Some studies start from the DE's effects in reducing micro-individual-firm costs, arguing that the main impacts of the DE on firms are the reduction of marginal, search, tracking, transportation, and validation costs (Ghasemaghaei & Calic, 2019); There is additional research on how the DE affects a firm's output efficiency and innovation capacity perspective, confirming that information technology not only has a favorable impact on several aspects of firms' R&D investment, product design, and process improvement, but also promotes firm's innovation initiative (Prokopenko et al., 2020). A small amount of literature has been studied in terms of increasing the likelihood of entrepreneurship, arguing that Internet use can increase entrepreneurship rates through, among other things, information channels and social interaction effects, and in doing so, stimulate economic dynamism and bolster economic growth (Johansson et al., 2006; Gontareva et al., 2018). The consequences of DE on the environment have steadily come under academic scrutiny in recent times. Zhou et al.,(2021) argued that eastern China is particularly affected by China's digital economic development in terms of haze pollution reduction. Haze pollution can be reduced by changing the energy system and promoting innovation. Xu et al.,(2022) thought that through the effects of green development and inventive development, the digital economy reduces environmental degradation. Many scholars have studied the economic effects of the DE. Studies have been done, for instance, on how the DE affects low-carbon evolution. A thorough index of low-carbon industry development and an evaluation system for the amount of DE development were created by Wang et al. (2012). And the empirical research revealed that the DE has a substantial driving influence on the growth of low-carbon industry; Li et al. (2021b) claim that between 2003 and 2018, the level of cooperation between the environmental system and the DE system expanded and fluctuated. The DE's development has greatly lowered PM2.5. Li (2021a) investigated the relationship between energy structure, DE, and CE empirically. The findings showed that CE are significantly driven by the coal-based energy structure, and that as DE advances, this relationship steadily weakens. By combing through the literature, there have been many relevant studies on CEE and DE both at home and abroad in recent years, but rarely have they been included in the same framework for analysis. Considering current study findings, DE can promote economic growth and reduce CE, which promotes the growth of a low-carbon economy. Therefore, Hypothesis 1 is put forward.

Hypothesis 1: The DE significantly influences the CEE.

The implementation of digital technologies has had a tremendous impact on reducing emissions across all industries, especially in the energy industry. Both the supply and demand sides of the energy system concurrently reflect the effect of the DE. On the supply side, digital technologies keep track of data from the energy production chain to reduce production risks, forewarn workers of them, and boost the effectiveness of the traditional fossil energy sector's production. Digital technologies thus ensure the secure and effective operation of energy systems and lower the level of environmental harm. (Chen, 2020; Soares and Tolmasquim, 2000; Rademaeker et al., 2014). On the demand side, in areas such as self-diagnosis, satellite navigation, entertainment systems, critical infrastructure, and transportation systems, digital technology can be leveraged to improve the effectiveness of energy consumption and usage throughout society. The usage of digital transportation systems in fields like smart homes, cars, and appliances enhances energy efficiency. (Aydin et al., 2018). By dematerializing human activities and communication, the DE also lowers the demand for energy and raw resources. (Heiskanen et al., 2005). For instance, online offices decreased public travel and hence decreased energy use during the New Crown Pneumonia pandemic. The information integration effect of the DE generally lessens the informational asymmetries among demand and availability. Wu et al. (2016) came to the same conclusion that increased energy intensity causes pollution. As a result, the high domestic energy consumption continues to be a significant barrier to CEE advancement. The incorporation and infiltration of DE in the domain of energy consumption would help to concurrently improve the efficiency of energy use amongst demand and availability, effectively promoting a low-carbon economy. The hypothesis 2 is put out in this work based on the analysis presented above.

Hypothesis 2: The advancement of DE improves CEE by lowering energy intensity.

According to Guan et al. (2022), the growth of the DE has a considerable impact on the quantity and quality of industrial structures being upgraded. The examination of the mechanisms demonstrates that by elevating the level of regional innovation, the DE can speed up the transition and modernization of industrial structures. Liu et al. (2022) argues that the DE has positively influenced China's Green Total Factor Productivity (GTFP) When viewed dynamically over the long term, and the modernization of industrial structures is a major transfer mechanism for the DE to support GTFP. Xi & Zhai (2022) argue that natural resource inequality causes differing levels of economic development and industrial structure modernization in eastern and western regions, as well as varying effects on environmental pollution. Environmental pollution is positively impacted by economic growth and the modernization of the industrial structure, and these two variables have an inverted U-shaped relationship. The panel threshold model's findings demonstrate that improving industrial structure can reduce the beneficial effects of economic expansion on environmental pollution. According to Zhao et al. (2022), industrial structure upgrading in China has risen progressively, and through increasing energy efficiency, it has a large spatially negative association with CO_2 emissions.The following possibilities are put out in light of the analyses just mentioned.

Hypothesis 3: The DE indirectly enhances CEE by promoting industrial structure upgrading.

Miller and Wilsdon (2001) noted that the DE symbolizes a technological revolution and is a key driver of technical progress. Almost all industries' value chains have undergone a fundamental business change as a result of digital technologies. (Yuan et al., 2021). Alam and Murad (2020) found that sing technology more effectively can advance the creation and application of renewable energy. Through precise 3D modeling of environmental and geographic factors, digital technologies accelerate the development of renewable energy and increase R&D effectiveness. Digital technology have been used to create new energy sources that are similar to conventional fossil fuel sources. These tools help employees perceive data more precisely, forecast weather changes, and utilize cleaner energy more often. Additionally, by facilitating the transformation of the energy consumption structure and helping governments in regulating the overall supply of energy through cross-subsidies and price controls, governments may more effectively reduce CE (Bhattacharya et al.,2015) . Xie et al. (2021) measured the CEE of 59 nations between 1998 and 2016 using a super-SBM model, and then they examined the various effects of technological advancement on the CEE of countries with various levels of efficiency. Technological advancement will encourage CEE to make considerable improvements. Additionally, it is shown that the interaction of technological development and energy intensity has intricate effects on CEE, highlighting the necessity of swiftly converting scientific and technological advancements into productivity in order to lessen the negative environmental consequences of emissions and pollutants. The fourth theory is suggested in this study based on the analyses shown above.

Hypothesis 4: The DE advances CEE through encouraging the development of green technologies.

3. Study Design

3.1. Model construction

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In this paper, the following economic model is created to ascertain how DE and CEE are related.

$$\mathrm{CEE}_{it} = \beta_0 + \beta_1 CEE_{it-1} + \beta_2 DE_{it} + \sum_{i=3}^{n} \beta_n X_{it} + \varepsilon_{it} \quad (3)$$

where i and t represent city and year, respectively. CEE is the dependent variable describing the performance of CE within the essay. DE is the primary factor that explains the traits of the digital economy. X is the control variable that contains marketization process (mark), urbanization rate (urb), and openness level (open). ε is the random error term.

The spatial regression models fully take into account the dependence between spatial units, thus modifying the traditional econometric model. The emergence of DE in a region not only affects local CE performance, but also has an impact on nearby areas or areas with closer connections due to spatial spillover effects. To examine the spatial impacts of DE on CEE in each province, relating to the study of LeSage et al (2010), The SDM in this research looks like this.

$$\mathrm{CEE}_{it} = \rho W \cdot \mathrm{CEE}_{it} + \alpha_1 \mathrm{DE}_{it} + \alpha_2 W \cdot \mathrm{DE}_{it} + \sum \beta X_{it} + \sum \theta W X_{it} + \mu_t + \delta_t + \varepsilon_{it} \quad (4)$$

where, ϱ is the lagged regression coefficient of spatial explained variables, $\alpha_1$is the coefficient of explanatory variables DE, α_2 is the product coefficient of DE and spatial weight matrix; W denotes the economic spatial weight matrix; θ is the coefficient of the control variable and the spatial economic matrix. Because the research goal of this paper may have spillover effects between regions with frequent economic exchanges or strong economic correlation, this work builds the economic spatial weight matrix, which may better describe the level of economic correlation between areas.The economic spatial weight matrix is chosen as the economic weight matrix for this work because the research goal may have spillover effects between regions with frequent trade and investment or high economic correlation.

To gain insight into the inner mechanism between DE and CEE. This research alludes the study of Wu et al (2021) and constructs the mediating effect model as follows.

$$\mathrm{CEE}_{i,t} = \alpha_0 + \alpha_1 D_{i,t} + \alpha_n X_{i,t} + \varepsilon_{i,t}$$

$$\mathrm{M}_{i,t} = \varphi_0 + \varphi_1 \mathrm{D}_{i,t} + \varphi_n X_{i,t} + \varepsilon_{i,t}$$

$$\mathrm{CEE}_{i,t} = \vartheta_0 + \vartheta_1 \mathrm{D}_{i,t} + \vartheta_2 \mathrm{M}_{i,t} + \vartheta_n X_{i,t} + \varepsilon_{i,t} \quad (5)$$

where M is an intermediate variable including energy intensity (Energy), industrial structure upgrading (Ind) and technological innovation effect (Tech), and other variables are set the same as in equation (3).

3.2. Variable measures and descriptions

3.2.1. Explanatory variables

This paper builds a CEE measuring system based on the Super-SBM model utilizing DEA Solver Pro 5.0 software, as indicated in Table 1, and draws inspiration from the research of Ge et al. (2022), the CEE in 30 Chinese provinces, municipalities, and autonomous areas was measured from 2007 to 2019. The "perpetual inventory approach" utilized to compute the capital stock using 2006 as the base date. The overall workforce across the three industries for the current year is chosen to be measured for labor force indicators. The expected output is the GDP of each province, and the real GDP of each region is deflated by taking 2006 as the base period to account for price changes. The CE of each province make up the undesirable output factor, and the measurement follows the methodology established in the IPCC Guidelines for National Greenhouse Gas Inventories from 2006.

Table 1. CEE measurement system for 30 provinces in mainland China.

	Indicator Name	Proxy variables	Unit of measure
Input elements	Capital	Capital stock (K)	Billion
	Workforce	Employment in the three industries (L)	10,000 people

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	Energy	Energy consumption (E)	million tons of standard coal
Output elements	Actual output	Real GDP (GDP)	Billion
Non-desired output elements	CE	CE (CO_2)	million tons

3.2.2. Core explanatory variables

Digital economy (DE). The comprehensive index of DE is computed using the entropy value technique, and it serves as the main explanatory factor in this study. Drawing on the index system for evaluation of Wang et al (2021), the construction of digital infrastructure, the development dimension of digital technology application, and the production service dimension of DE are the three criteria used to determine the level of DE, and Table 2 displays the specific indexes.

Table 2. Comprehensive index system of DE.

	Evaluation Dimension	Indicator System
The Level of DE	The construction of digital infrastructure	Internet usage percentage
		Port accesses to the Internet
		Ratio of people using cellphones
		Total number of mobile phone users
	The construction of digital technology application	Users of the internet
		Quantity of Domains
		Quantity of websites
	The construction of digital production services	Computer and software workers as a proportion of the urban population
		Overall telecom services per capita
		Revenue from the software industry as a share of GDP
		E-commerce purchases and sales as a percentage of GDP
		Digital Finance Development Index

3.2.3. Mediating variables

Energy intensity (Energy). Energy intensity, also known as integrated energy consumption intensity, is a crucial barometer of economic and social growth, and it is computed by dividing each province's total energy consumption by its GDP referring to the research by Wu et al (2016). By translating the actual regional usage of fossil fuels like oil, coal, and natural gas into similar standard coal and adding them together, it is possible to determine each province's overall energy consumption.

Industrial structure upgrading (Ind). The tertiary industry's growth rate has significantly increased in this stage of industrial development due to the economy's ongoing growth and the ongoing restructuring of the industrial structure. According to Liu et al. (2021), The upgrading of the industrial structure is measured in this study using the ratio of the tertiary sector's value added to the secondary sector's value added.

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Technological innovation (Tech). The innovation indicator of the Chinese Cities and Industries Innovation Capability Report was chosen to measure technological innovation (Yang et al., 2021). This indicator has the following advantages: First, the bias brought on by duplicate counting of innovation inputs and outputs is first corrected by using the value of patents as innovation output data. Second, by employing the patent renewal model to calculate the anticipated value of patents over a range of years, it also tackles the problem that the direct measurement of innovation level by the number of patents does not accurately reflect the potential value of patents and patent quality.

3.2.4. Control variables

In the empirical study, to increase the validity of the research, this paper selects marketization process (mark), urbanization rate (urb), and openness level (open) as control variables. Among them, marketization process (mark) with reference to a research of Zeng et al.(2021)and is expressed using marketization index; urbanization rate refers to the study of Li & Ma, (2014) and is expressed as the percentage of the population that does not work in agriculture in each province; Referring to the research of Wang et al.(2022), openness level is calculated as the overall import/export ratio to GNP, and its proportion size indicates the degree of openness.

3.3. Data sources and descriptive statistics

The full text is based on sources from the website of the National Bureau of Statistics, the websites of local statistical bureaus, the China Statistical Yearbook, the China Energy Statistical Yearbook, the China Marketization Index and the statistical yearbooks of each province, and the report of Digital Inclusive Finance Development Index by the Digital Finance Research Center of Peking University. This study used the linear interpolation method to fill in the gaps created by missing data for specific years in various provinces, and Table 3 displays the descriptive statistics for the key variables.

Table 3. Descriptive statistics of main variables.

Variable	Obs	Mean	Std.Dev	Min	Max
CEE	270	0.433	0.265	0.005	1.217
DE	270	0.245	0.129	0.040	0.703
mark	270	6.721	1.956	2.067	11.639
urb	270	0.572	0.122	0.311	0.896
open	270	5.598	1.545	-0.301	7.724

4. Empirical analysis

4.1. Baseline regression analysis

Table 4(1)-(2) displays the effect of DE on CEE calculated using the fixed effects model. As can be observed, there is a strong positive correlation between DE and CEE, suggesting that a rise in DE will greatly advance CEE. Table 4(3)-(4) shows the empirical results of using the system GMM model to examine the impact of DE on CEE, and it is found that DE significantly promotes CEE. Hypothesis 1 holds. And the one-period lagged term of CEE is positively noticeable at the 1% level on the current period CEE, then the residual term following differencing exhibits first-order autocorrelation but not second-order autocorrelation, which meets the requirement of systematic generalized moment estimation; Considering the findings of the Hansen test, none of the instrumental variables are invalid and there is no over-identification.

Regarding the control variables, the degree of marketization (mark) significantly improves CEE in the whole country, eastern provinces and central and western provinces, could be because the deepening of marketization reform breaks down barriers between markets, bringing more

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technology exchanges, learning effects between enterprises and the progress and diffusion of environmental protection technologies leading to the decrease of CE. The urbanization level (urb) has a a favorable impact on CEE, probably because the advancement of urbanization will lead to the transfer of surplus agricultural labor to non-agricultural industries, which is conducive to the increase of the scale and intensification of agricultural production, optimizing the industrial structure and resource allocation efficiency while generating economies of scale, making it possible to increase the output per unit of CE, which encourages a growth in CEE. Openness level (open) is not significant on CEE at the national level, possibly because trade opening to the outside world increases China's carbon intensity and emissions, and overall the bottom-line racing impact of allowing access to the outside is greater than the environmental gain effect of trade. Industries with high pollution levels were relocated from nations with rigorous environmental restrictions to China, which has laxer environmental regulations, and China became a pollution refuge for developed countries.

Table 4. Baseline regression and regional heterogeneity regression results.

CEE	(1) FE	(2) FE	(3) GMM	(4) GMM
L.CEE			0.508***	0.176***
			(0.006)	(0.028)
DE	1.573***	0.942***	0.844***	0.853***
	(0.078)	(0.109)	(0.021)	(0.096)
mark		0.020**		0.097***
		(0.008)		(0.010)
urb		0.688***		0.535***
		(0.093)		(0.116)
open		-0.014*		-0.127***
		(0.008)		(0.007)
_cons	0.048**	-0.245***		0.026***
	0.021	(0.042)		(0.033)
AR(2)			0.388	0.317
Hansen			0.633	0.851
N	270	270	240	240

*** p<0.01, ** p<0.05, * p<0.1，robust standard errors in parentheses

4.2. Regional heterogeneity analysis

Regression analyses for the eastern, central and western regions of China are exhibited in Tables 5(1) and (2), and the test findings demonstrate that the DE in the eastern region has a notable influence on CEE, which is in accordance with the regression results for the whole province, but the impact of DE on CEE in the central and western regions is not notable, which may be for the reason that the eastern region has a better industrial base, technological capability and demand orientation than the central and western regions, because of this, the eastern region is the only one where DE has a greater impact on the growth of a low-carbon economy. The cut-off sample according to the median of per capita GDP, divided into the high degree of economic region samples and low degree of economic development samples, respectively on the relationship between DE and CEE again do regression analysis, the empirical results such as Table 5 (3) and (4), it can be seen that DE in high economic development level significantly increased the CEE, however, the low economic development level of 1% reduces the CEE. The possible reason is that the later regions may continue the crude development

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mode of high pollution and high consumption, which will bring more carbon emissions while the GDP growth, thus reducing CEE.

Table 5. Regional heterogeneity regression results.

CEE	(1) East	(2) Midwest	(3) High economic development level	(4) Low economic development level
DE	1.160***	-0.218	1.036***	-0.420*
	(7.18)	(-0.99)	(0.142)	(0.240)
mark	0.0380*	0.0221**	0.006	0.019**
	(2.50)	(2.89)	(0.012)	(0.009)
urb	0.819***	-0.027	0.860***	-0.096
	(6.09)	(-0.22)	(0.136)	(0.121)
open	-0.069**	0.020*	-0.017	0.029***
	(-3.31)	(2.47)	(0.016)	(0.009)
_cons	-0.210*	0.163**	-0.329***	0.222**
	(-2.09)	(2.69)	(0.091)	(0.060)
N	108	162	135	135
Adj R-sq	0.818	0.711	0.833	0.602

*** p<0.01, ** p<0.05, * p<0.1， robust standard errors in parentheses

4.3. Robustness tests based on the SDM

Within the essay, we explore the geographical clustering status of the model's explanatory and explained variables through the Moran's I and utilize it to assess the spatial autocorrelation of the variables, drawing on the study of Meng et al. (2022). As demonstrated by Table 6, in the observation period of 2011-2019, the observed values of DE and CEE are positive, and both may deny the initial hypothesis of no spatial connection at the 1% degree of significance (except for CEE in 2018), which indicates that the observed values of the two have a considerable positive spatial association.

Table 6. Moran's I for DE and CEE.

year	Moran's I of DE	year	Moran's I of CEE
2011	0.552***	2011	0.626***
2012	0.521***	2012	0.638***
2013	0.463***	2013	0.646***
2014	0.497***	2014	0.662***
2015	0.455***	2015	0.678***
2016	0.433***	2016	0.597***
2017	0.437***	2017	0.628***
2018	0.392***	2018	-0.036
2019	0.365***	2019	0.615***

*** p<0.01, ** p<0.05, * p<0.1

Within this essay, we shall choose a spatial econometric model that is appropriate for this paper and evaluate its reliability. The study uses the approach described by LeSage et al. (2009)[46] to test whether there is spatial autocorrelation, the spatial autoregressive model passes the LM statistic and its robust form. Secondly, the Wald test is used to compare the applicability of the SDM; the LR statistic is constructed to verify again that the SDM cannot degrade into the spatial autoregressive model and the spatial error model. The results of the aforementioned experiments are presented in Table 7, and it is clear that the SDM is the best model.

Table 7. Identification and testing of spatial econometric models.

Method tests	Statistical value	Method tests	Statistical value
LM-lag	64.728***	Wald-SAR	85.21***
LM-lag(robust)	2.113	Wald-SEM	19.38***
LM-error	105.474***	LR-SAR	36.39***
LM-error(robust)	42.859***	LR-SEM	27.40***

* p < 0.10, ** p < 0.05, *** p < 0.01

The empirical studies are presented in Table 8 and are based on the tests mentioned above. This research uses the SDM for regression analysis. The main effect coefficient of DE was 0.918, at 1% level, which was substantial and favorable for CEE, and shows that hypothesis 1 holds. The DE's spillover coefficient is negative and notable, suggesting that a province's level of DE has a detrimental effect on the CEE of another province with high economic significance, which may be due to the fact that it's challenging to share the results of low-carbon technology innovation between provinces as a result of the regional safeguarding intellectual property rights, making the development of a low-carbon economy in the province is greatly aided by the rise of the DE, while hindering the construction of low-carbon economy in a province with high economic relevance. Among the control variables, the degree of marketization has a notable favourable effect on the CEE of this province, which is accordance with the previous empirical results, but it has a detrimental impact on the CEE of economically connected provinces, probably due to the existence of a certain competition between provinces. The openness level has a profoundly adverse impact on the CEE of the province, but not on the CEE of the economically related provinces.

Table 8. Spatial Durbin model regression results.

CEE	(1)	(2)	(3)	(4)
DE	1.202***	1.089***	0.884***	0.918***
	(0.0691)	(0.0927)	(0.0984)	（0.009）
mark		0.0183***	0.0153***	0.022***
		(0.00533)	(0.00530)	（0.007）
urb			0.237**	0.199*
			(0.111)	（0.112）
lnopen				-0.012*
				（0.007）
W*DE	-0.253*	-0.0298	-0.397*	-0.411**
	(0.144)	(0.202)	(0.210)	（0.208）
W*mark		-0.0381***	-0.0533***	-0.063***
		(0.0131)	(0.0133)	（0.019）
W*urb			0.713***	0.749***
			(0.212)	（0.217）
W*lnopen				0.013
				（0.015）
rho	0.557***	0.614***	0.483***	0.494***

sigma2_e	0.0116***	0.0106***	0.0100***	0.010***
N	270	270	270	270

*** p<0.01, ** p<0.05, * p<0.1， robust standard errors in parentheses.

4.4. Test of mediating effect

The regression outcomes of the mediating effect model are displayed in Table 8, where Table 9(1), (2), and (3) provide the outcomes of a test to determine whether the DE has a mediating influence on the energy intensity of CEE. Regression (1) is consistent with previous conclusions, indicating that the DE markedly and favorably impacts the CEE. Regression (2) shows that the DE significantly reduces energy intensity, and the regression (3) demonstrates that the DE and energy intensity both help improve CEE, indicating that the DE can increase CEE by reducing energy intensity, supporting hypothesis 2; Table 9(1), (4) and (5) show the intermediary effects of technological innovation of the DE on CEE. The regression (4) shows that the DE significantly promotes technological innovation, and regression (5) shows that technological innovation is positively significant for CEE, and the DE is positively significant for CEE, indicating that the DE can promote technological innovation and thus enhance the partial mediating effect of CEE, thus verifying hypothesis 3; Table 9(1), (6) and (7) show the outcomes of the intermediary effects of the DE on the industrial structure upgrade of CEE. Regression (6) shows that the DE has a positive notable effects on the industrial structure upgrade(Ind), regression (7) shows that the Ind has a noticeable beneficial effects on CEE, and the DE continues to have a favorable effect on CEE, which indicates that the DE can improve the industrial structure upgrade and thus enhance the intermediary effect of CEE, thus verifying hypothesis 4.

Table 9. Mediating effect test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CEE	Energy	CEE	Tec	CEE	Ind	CEE
Energy/Tec/Ind			-0.145***		3.40e-05**		0.00319***
			(0.0226)		(1.49e-05)		(0.000767)
DE	0.942***	-0.721**	0.895***	4,766***	0.780***	45.09***	0.798***
	(0.109)	(0.301)	(0.110)	(453.0)	(0.130)	(8.632)	(0.112)
mark	0.0198**	-0.229***	-0.0156*	-78.14**	0.0224***	0.346	0.0186**
	(0.00821)	(0.0185)	(0.00846)	(33.99)	(0.00823)	(0.648)	(0.00797)
urb	0.688***	1.394***	0.890***	1,420***	0.640***	87.30***	0.410***
	(0.0927)	(0.237)	(0.0913)	(383.9)	(0.0944)	(7.315)	(0.112)
lnopen	-0.0143*	0.000137**	-2.75e-05	-46.72	-0.0127	-1.698**	-0.00884
	(0.00834)	(6.14e-05)	(2.24e-05)	(34.52)	(0.00830)	(0.658)	(0.00819)
_cons	-0.245***	1.663***	-0.0564	-833.9***	-0.216***	184.4***	-0.832***
	(0.0422)	(0.106)	(0.0536)	(174.6)	(0.0437)	(3.326)	(0.147)
N	270	270	270	270	270	270	270
year	control	control	control	control	control	control	control
R^2	0.799	0.629	0.835	0.545	0.803	0.697	0.811

5. Conclusion and Implications

Examining whether the DE may serve as a key understanding of energy saving and decarbonisation and so It has great theoretical and applied usefulness to strengthen CEE in the background of dual carbon and high-quality development in China. In view of this, this essay measured the CEE of 30 provinces in China from 2011-2019 according to the Super-SBM method, and then investigated the relationship and influence mechanism between the DE and CEE through the

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systematic GMM , SDM, and mediating effect model. We discover that (1) the DE improves CEE; (2) the mechanism study shows that the DE improves CEE by reducing energy intensity, promoting industrial upgrading and green technology innovation and thus; (3) an examination of regional heterogeneity reveals that the DE greatly raises CEE in the eastern provinces but not in the middle or western regions. DE improves CEE in provinces with high degree of economic development, but decreases CEE in provinces with low degree of economic development. As a result, the following recommendations for policy are made in this study.

First, firmly grasp the important strategic opportunity period for the construction of DE. Efforts should be made to promote the construction of digital infrastructure, digital technology application and digital production services to solidify the foundation of the DE. Both at once, we should accelerate the promotion of digital technology and knowledge popularization in the less developed regions in the central and western regions, and the government and enterprises can carry out cross-regional digital technology application and production management experience exchange, digital knowledge popularization education and various initiatives to reduce the disparity in development between provinces and regions and raise China's DE standards generally. Utilize the DE's potential to aid when a low-carbon economy expands in accordance with regional needs. Eastern regions should accelerate the construction of digital labor platforms under the premise of steadily realizing DE development to promote green technological innovation, while central and western regions should focus on encouraging DE development under the general principle of controlling systemic financial risks and appropriately and actively broadening digital investment and financing channels.

Secondly, we should promote economic transformation and upgrading with digitalization, make up for the shortcomings of industries around the country with the support of Internet technology, and encourage the general improvement and modernization of China's industrial structure. Agriculture should actively encourage the use of digital monitoring systems and online sales methods in the process of planting, producing and selling agricultural products. In industry, we should continue to modernize and improve existing production equipment and encourage the coordinated allocation of production factors. On the service side, first, we should increase investment in R&D and invention to lay the foundation of digital technology for all regions; second, We should keep advancing the growth of e-commerce and service industry integration, and link agriculture and industry digitization with service industry. Guide the real economy enterprises to take the initiative to apply and upgrade digital production equipment. Encourage the development, application and promotion of enterprise intelligent big data systems, enhance the ability and level of digital application at the front, middle and back ends of production, and promote low-carbon economic development with digital as the new driving force.

Third, strengthen regional technology linkages and resource sharing. Solving the difficulties faced by the DE in promoting the construction of low-carbon economy. China's DE started late and is now in a rapid development stage, and the phenomenon of uneven development is still more prominent. At the early stage of development, certain barriers are formed in information, knowledge, technology and innovation factors in order to safeguard their own development, which hinders resource sharing and is ultimately detrimental to the overall coordinated development of the region. In the digital era, cooperation is an inevitable choice for regional development. To this end, we should break the information technology barriers between provinces and regions, eliminate institutional barriers, smooth the flow of innovation factors, optimize the reasonable layout of resources in the region, strengthen the sharing of digital resources and talent exchange, accelerate technology dissemination and information exchange, and give full play to the development "dividends" brought by the DE ".

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